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(54) SYSTEM AND METHOD FOR ONLINE REAL-TIME MULTI- OBJECT TRACKING

(71) Applicant: **TUSIMPLE, INC.**, San Diego, CA (US)

(72) Inventors: **Lingting Ge**, San Diego, CA (US); **Pengfei Chen**, San Diego, CA (US); **Panqu Wang**, San Diego, CA (US)

(73) Assignee: **TUSIMPLE, INC.**, San Diego, CA (US)

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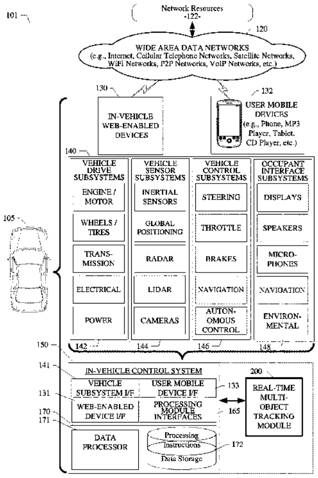
Primary Examiner — Ping Y Hsieh

(74) *Attorney, Agent, or Firm* — Paul Liu; Glenn Theodore Mathews Perkins Coie, LLP

(57) ABSTRACT

A system and method for online real-time multi-object tracking is disclosed. A particular embodiment can be configured to: receive image frame data from at least one camera associated with an autonomous vehicle; generate similarity data corresponding to a similarity between object data in a previous image frame compared with object detection results from a current image frame; use the similarity data to generate data association results corresponding to a best matching between the object data in the previous image frame and the object detection results from the current image frame; cause state transitions in finite state machines for each object according to the data association results; and provide as an output object tracking output data corresponding to the states of the finite state machines for each object.

20 Claims, 6 Drawing Sheets



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See application file for complete search history.

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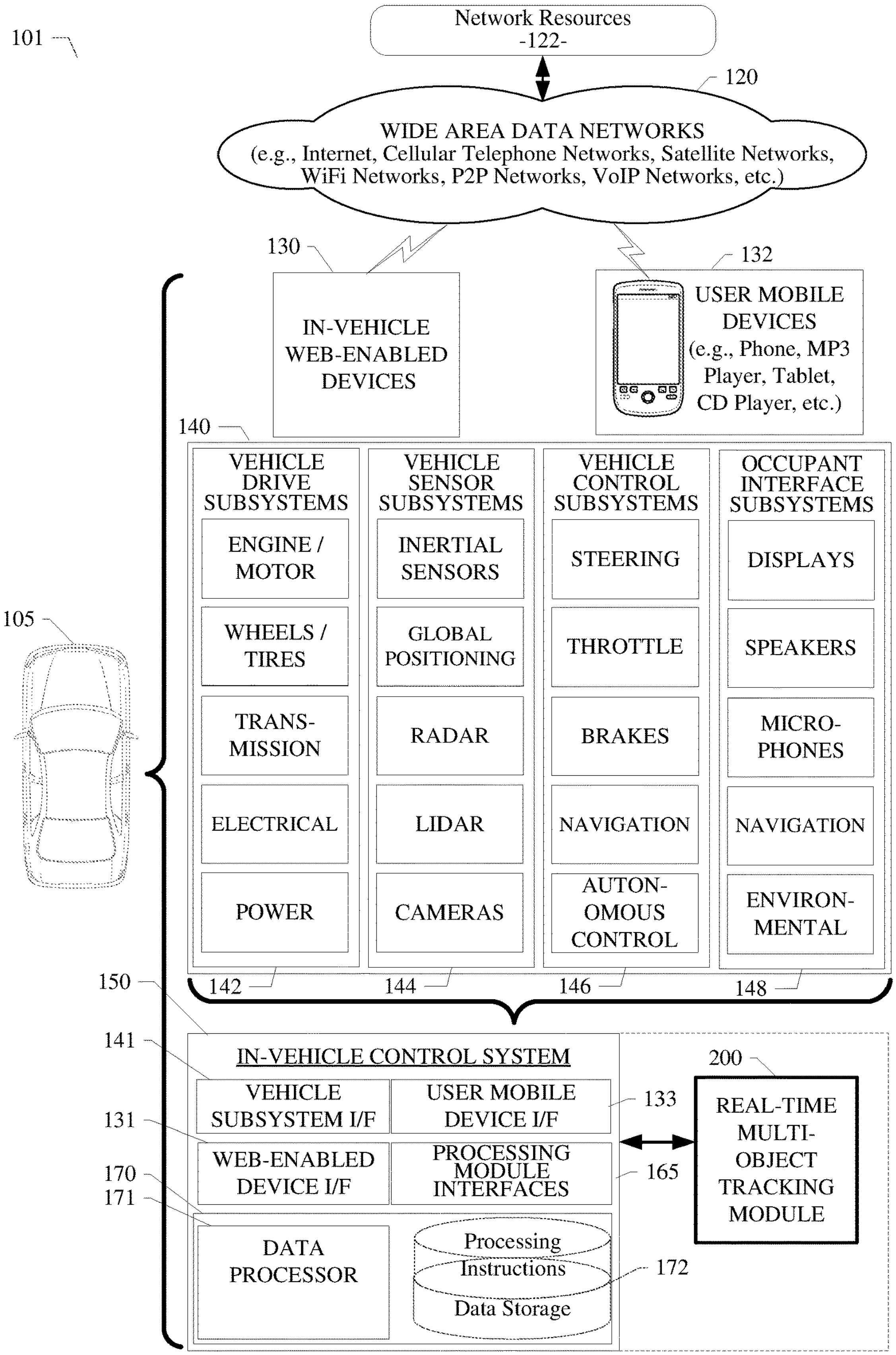
101
Network Resources
-122-
120
WIDE AREA DATA NETWORKS
(e.g., Internet, Cellular Telephone Networks, Satellite Networks,
WiFi Networks, P2P Networks, VoIP Networks, etc.)
130
132
IN-VEHICLE WEB-ENABLED DEVICES
USER MOBILE DEVICES (e.g., Phone, MP3 Player, Tablet, CD Player, etc.)
140
105
VEHICLE DRIVE SUBSYSTEMS
ENGINE / MOTOR
WHEELS / TIRES
TRANS-MISSION
ELECTRICAL
POWER
VEHICLE SENSOR SUBSYSTEMS
INERTIAL SENSORS
GLOBAL POSITIONING
RADAR
LIDAR
CAMERAS
VEHICLE CONTROL SUBSYSTEMS
STEERING
THROTTLE
BRAKES
NAVIGATION
AUTON-OMOUS CONTROL
OCCUPANT INTERFACE SUBSYSTEMS
DISPLAYS
SPEAKERS
MICRO-PHONES
NAVIGATION
ENVIRON-MENTAL
142
144
146
148
150
141
131
170
171
IN-VEHICLE CONTROL SYSTEM
VEHICLE SUBSYSTEM I/F
USER MOBILE DEVICE I/F
133
WEB-ENABLED DEVICE I/F
PROCESSING MODULE INTERFACES
165
DATA PROCESSOR
Processing Instructions
Data Storage
172
200
REAL-TIME MULTI-OBJECT TRACKING MODULE

Fig. 1

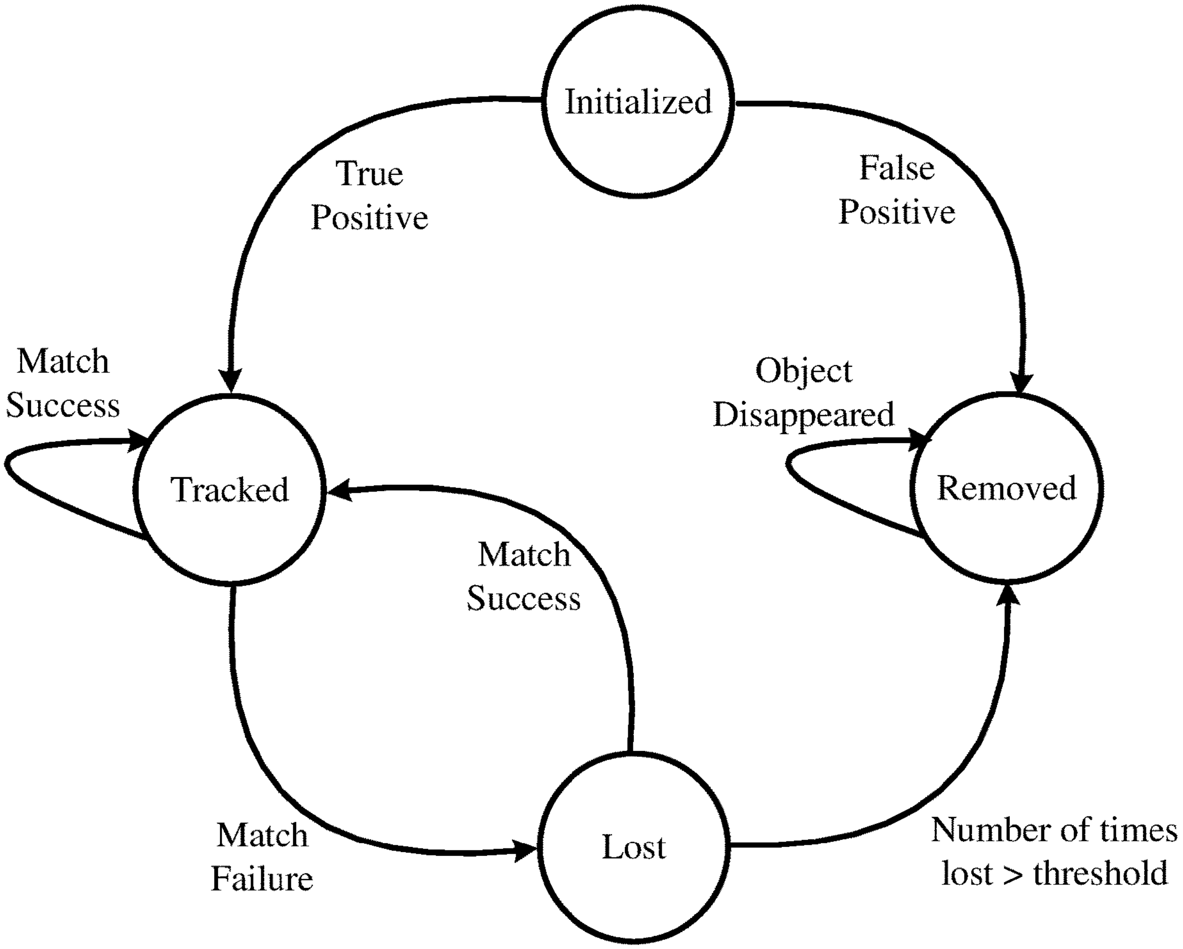
Initialized
True Positive
False Positive
Match Success
Tracked
Object Disappeared
Removed
Match Success
Match Failure
Lost
Number of times lost > threshold

Fig. 2

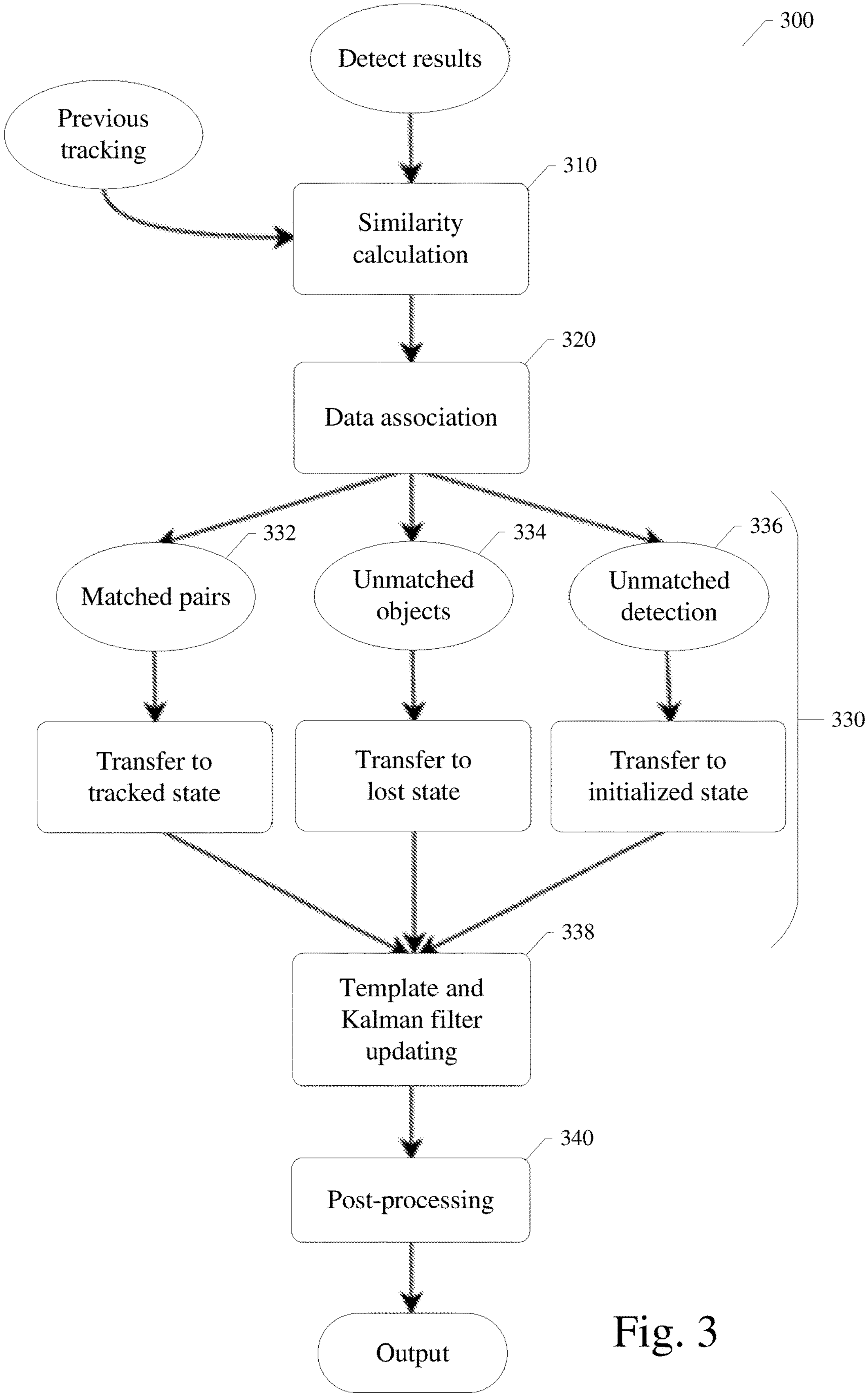
300
Detect results
Previous tracking
310
Similarity calculation
320
Data association
332
334
336
Matched pairs
Unmatched objects
Unmatched detection
330
Transfer to tracked state
Transfer to lost state
Transfer to initialized state
338
Template and Kalman filter updating
340
Post-processing
Output

Fig. 3

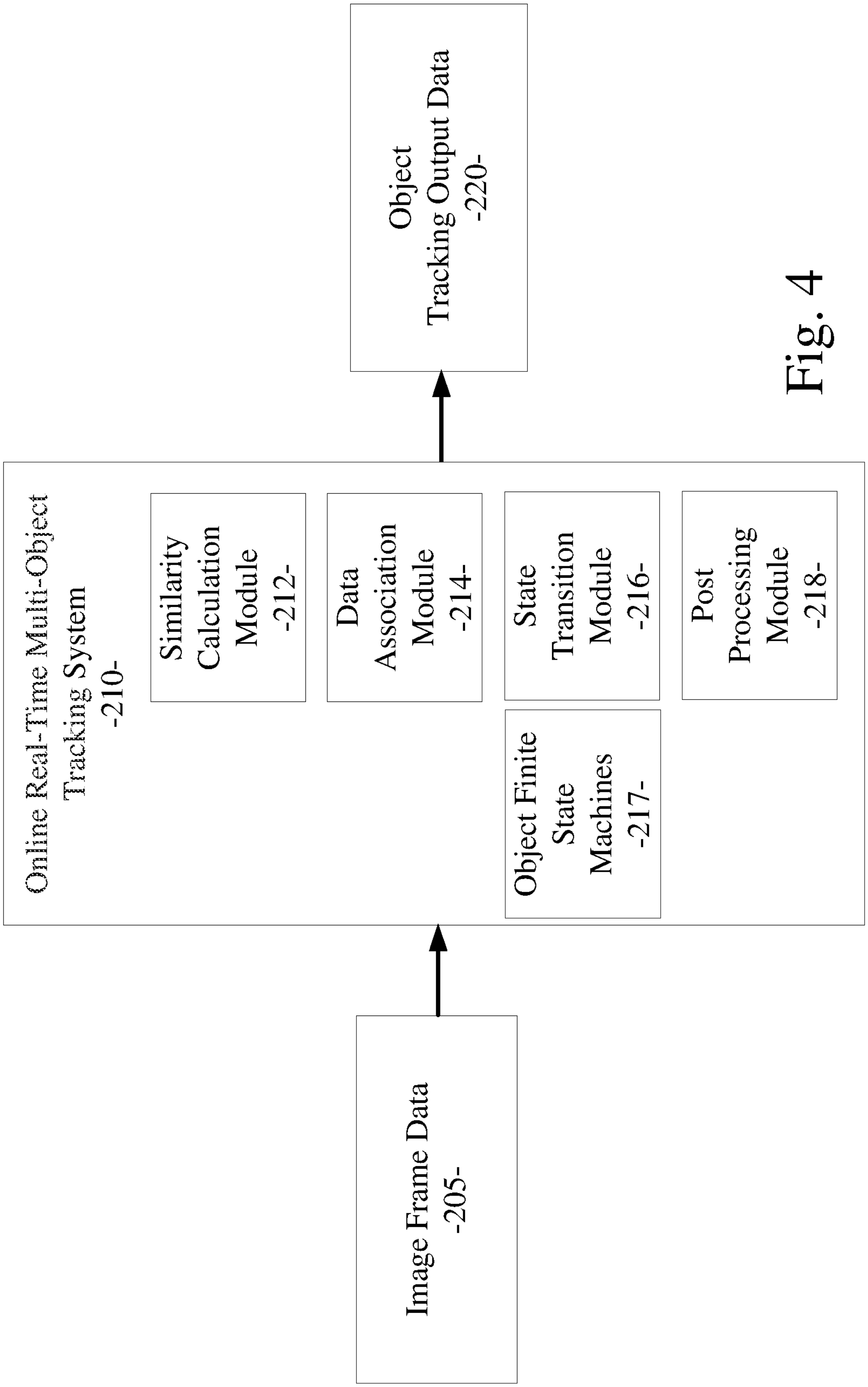
Image Frame Data
-205-
Online Real-Time Multi-Object Tracking System
-210-
Similarity Calculation Module
-212-
Data Association Module
-214-
State Transition Module
-216-
Object Finite State Machines
-217-
Post Processing Module
-218-
Object Tracking Output Data
-220-

Fig. 4

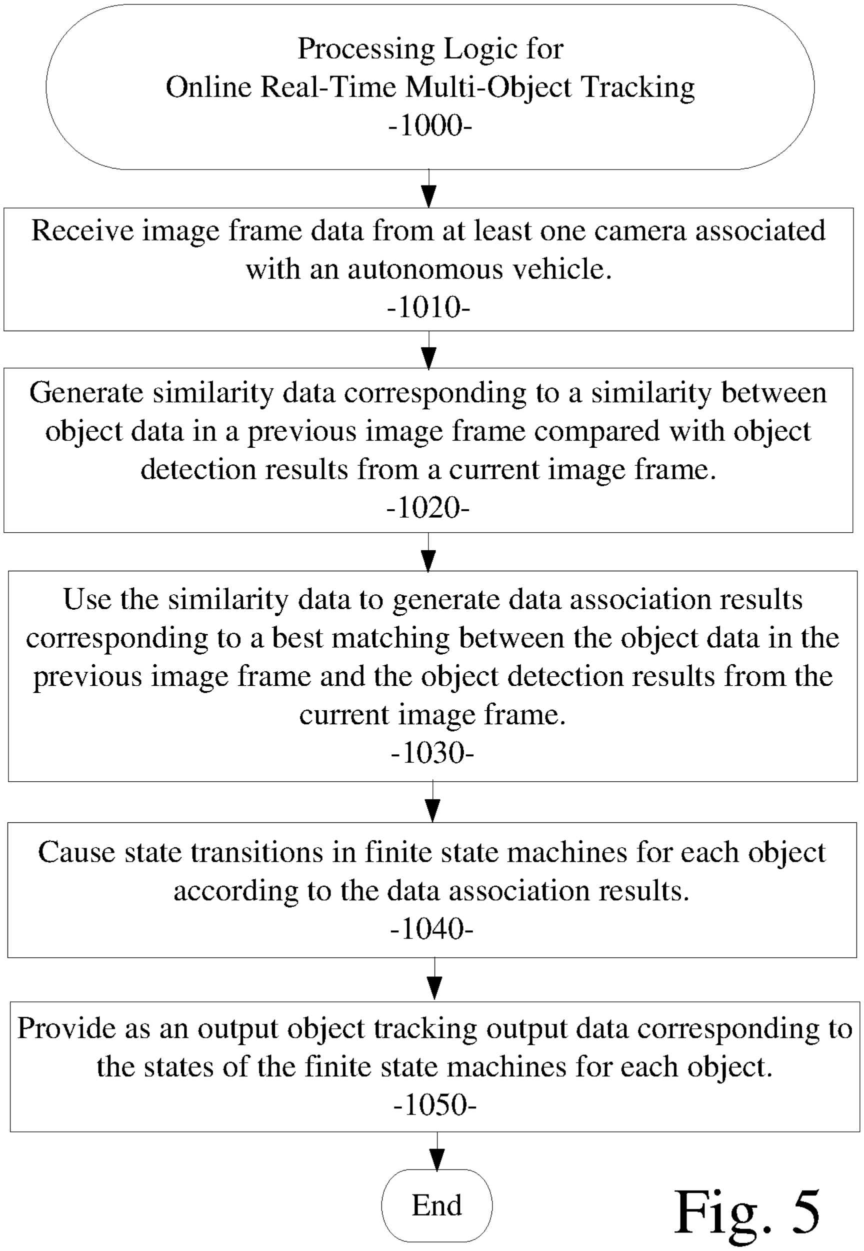
Processing Logic for
Online Real-Time Multi-Object Tracking
-1000-
Receive image frame data from at least one camera associated with an autonomous vehicle.
-1010-
Generate similarity data corresponding to a similarity between object data in a previous image frame compared with object detection results from a current image frame.
-1020-
Use the similarity data to generate data association results corresponding to a best matching between the object data in the previous image frame and the object detection results from the current image frame.
-1030-
Cause state transitions in finite state machines for each object according to the data association results.
-1040-
Provide as an output object tracking output data corresponding to the states of the finite state machines for each object.
-1050-
End

Fig. 5

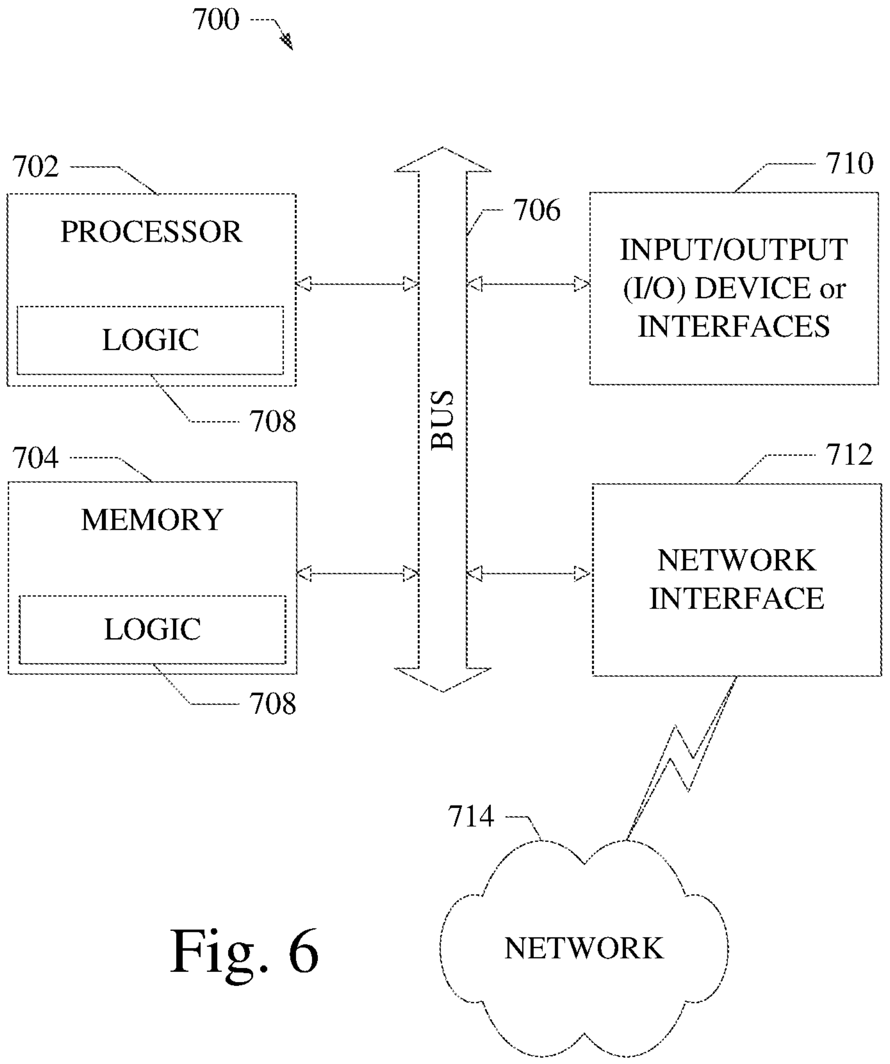
700
702
PROCESSOR
LOGIC
708
704
MEMORY
LOGIC
708
BUS
706
710
INPUT/OUTPUT (I/O) DEVICE or INTERFACES
712
NETWORK INTERFACE
714
NETWORK

Fig. 6

SYSTEM AND METHOD FOR ONLINE REAL-TIME MULTI- OBJECT TRACKING

CROSS-REFERENCE TO RELATED APPLICATION

This application is a continuation of U.S. patent application Ser. No. 16/868,400, filed May 6, 2020, which is a continuation of U.S. patent application Ser. No. 15/906,561, filed Feb. 27, 2018, each of which is incorporated by reference herein in its entirety.

TECHNICAL FIELD

This patent document pertains generally to tools (systems, apparatuses, methodologies, computer program products, etc.) for image processing, object tracking, vehicle control systems, and autonomous driving systems, and more particularly, but not by way of limitation, to a system and method for online real-time multi-object tracking.

BACKGROUND

Multi-Object Tracking (MOT) is a popular topic in computer vision that has received lots of attention over past years in both research and industry. MOT has a variety of applications in security and surveillance, video communication, and self-driving or autonomous vehicles.

Multi-object tracking can be divided into two categories: online MOT and offline MOT. The difference between these two kinds of tracking is that online tracking can only use the information of previous image frames for inference, while offline tracking can use the information of a whole video sequence. Although offline tracking can perform much better than online tracking, in some scenarios such as self-driving cars, only online tracking can be used; because, the latter image frames cannot be used to perform inference analysis for the current image frame.

Recently, some online MOT systems have achieved state-of-the-art performance by using deep learning methods, such as Convolutional Neural Networks (CNN) and Long Short Term Memory (LSTM). However, all these methods cannot achieve real-time speed while maintaining high performance. Moreover, other purported real-time online MOT systems, such as those using only Kalman filters or a Markov Decision Process (MDP), also cannot achieve enough performance to be used in practice. Therefore, an improved real-time online MOT system with better performance is needed.

SUMMARY

A system and method for online real-time multi-object tracking are disclosed. In various example embodiments described herein, we introduce an online real-time multi-object tracking system, which achieves state-of-the-art performance at a real-time speed of over 30 frames per second (FPS). The example system and method for online real-time multi-object tracking as disclosed herein can provide an online real-time MOT method, where each object is modeled by a finite state machine (FSM). Matching objects among image frames in a video feed can be considered as a transition in the finite state machine. Additionally, the various example embodiments can also extract motion features and appearance features for each object to improve tracking performance. Moreover, a Kalman filter can be used to reduce the noise from the results of the object detection.

In the example embodiment, each object in a video feed is modeled by a finite state machine, and the whole tracking process is divided into four stages: 1) similarity calculation, 2) data association, 3) state transition, and 4) post processing. In the first stage, the similarity between an object template or previous object data and an object detection result is calculated. Data indicative of this similarity is used for data association in the second stage. The data association of the second stage can use the similarity data to find the optimal or best matching between previous object data and the object detection results in the current image frame. Then, each object transitions its state according to the results of the data association. Finally, a post processing operation is used to smooth the bounding boxes for each object in the final tracking output.

BRIEF DESCRIPTION OF THE DRAWINGS

The various embodiments are illustrated by way of example, and not by way of limitation, in the figures of the accompanying drawings in which:

FIG. **1** illustrates a block diagram of an example ecosystem in which an in-vehicle image processing module of an example embodiment can be implemented;

FIG. **2** illustrates a single object modeled by a finite state machine, and a method used in an example embodiment to perform multi-object tracking;

FIG. **3** is an operational flow diagram illustrating an example embodiment of a system and method for online real-time multi-object tracking;

FIG. **4** illustrates components of the system for online real-time multi-object tracking of an example embodiment;

FIG. **5** is a process flow diagram illustrating an example embodiment of a system and method for online real-time multi-object tracking; and

FIG. **6** shows a diagrammatic representation of machine in the example form of a computer system within which a set of instructions when executed may cause the machine to perform any one or more of the methodologies discussed herein.

DETAILED DESCRIPTION

In the following description, for purposes of explanation, numerous specific details are set forth in order to provide a thorough understanding of the various embodiments. It will be evident, however, to one of ordinary skill in the art that the various embodiments may be practiced without these specific details.

As described in various example embodiments, a system and method for online real-time multi-object tracking are described herein. An example embodiment disclosed herein can be used in the context of an in-vehicle control system **150** in a vehicle ecosystem **101**. In one example embodiment, an in-vehicle control system **150** with a real-time multi-object tracking module **200** resident in a vehicle **105** can be configured like the architecture and ecosystem **101** illustrated in FIG. **1**. However, it will be apparent to those of ordinary skill in the art that the real-time multi-object tracking module **200** described and claimed herein can be implemented, configured, and used in a variety of other applications and systems as well.

Referring now to FIG. **1**, a block diagram illustrates an example ecosystem **101** in which an in-vehicle control system **150** and a real-time multi-object tracking module **200** of an example embodiment can be implemented. These components are described in more detail below. Ecosystem

101 includes a variety of systems and components that can generate and/or deliver one or more sources of information/data and related services to the in-vehicle control system **150** and the real-time multi-object tracking module **200**, which can be installed in the vehicle **105**. For example, a camera installed in the vehicle **105**, as one of the devices of vehicle subsystems **140**, can generate image and timing data (e.g., a video feed) that can be received by the in-vehicle control system **150**. One or more of the cameras installed in the vehicle **105** can be forward-facing or laterally-facing or oriented to capture images on a side of the vehicle **105**. The in-vehicle control system **150** and the real-time multi-object tracking module **200** executing therein can receive this image and timing data or video feed input. As described in more detail below, the real-time multi-object tracking module **200** can process the image input and extract object features, which can be used by an autonomous vehicle control subsystem, as another one of the subsystems of vehicle subsystems **140**. The autonomous vehicle control subsystem, for example, can use the real-time extracted object features to safely and efficiently navigate and control the vehicle **105** through a real world driving environment while avoiding obstacles and safely controlling the vehicle.

In an example embodiment as described herein, the in-vehicle control system **150** can be in data communication with a plurality of vehicle subsystems **140**, all of which can be resident in a user's vehicle **105**. A vehicle subsystem interface **141** is provided to facilitate data communication between the in-vehicle control system **150** and the plurality of vehicle subsystems **140**. The in-vehicle control system **150** can be configured to include a data processor **171** to execute the real-time multi-object tracking module **200** for processing image data received from one or more of the vehicle subsystems **140**. The data processor **171** can be combined with a data storage device **172** as part of a computing system **170** in the in-vehicle control system **150**. The data storage device **172** can be used to store data, processing parameters, and data processing instructions. A processing module interface **165** can be provided to facilitate data communications between the data processor **171** and the real-time multi-object tracking module **200**. In various example embodiments, a plurality of processing modules, configured similarly to real-time multi-object tracking module **200**, can be provided for execution by data processor **171**. As shown by the dashed lines in FIG. **1**, the real-time multi-object tracking module **200** can be integrated into the in-vehicle control system **150**, optionally downloaded to the in-vehicle control system **150**, or deployed separately from the in-vehicle control system **150**.

The in-vehicle control system **150** can be configured to receive or transmit data from/to a wide-area network **120** and network resources **122** connected thereto. An in-vehicle web-enabled device **130** and/or a user mobile device **132** can be used to communicate via network **120**. A web-enabled device interface **131** can be used by the in-vehicle control system **150** to facilitate data communication between the in-vehicle control system **150** and the network **120** via the in-vehicle web-enabled device **130**. Similarly, a user mobile device interface **133** can be used by the in-vehicle control system **150** to facilitate data communication between the in-vehicle control system **150** and the network **120** via the user mobile device **132**. In this manner, the in-vehicle control system **150** can obtain real-time access to network resources **122** via network **120**. The network resources **122** can be used to obtain processing modules for execution by data processor **171**, data content to train internal neural networks, system parameters, or other data.

The ecosystem **101** can include a wide area data network **120**. The network **120** represents one or more conventional wide area data networks, such as the Internet, a cellular telephone network, satellite network, pager network, a wireless broadcast network, gaming network, WiFi network, peer-to-peer network, Voice over IP (VoIP) network, etc. One or more of these networks **120** can be used to connect a user or client system with network resources **122**, such as websites, servers, central control sites, or the like. The network resources **122** can generate and/or distribute data, which can be received in vehicle **105** via in-vehicle web-enabled devices **130** or user mobile devices **132**. The network resources **122** can also host network cloud services, which can support the functionality used to compute or assist in processing image input or image input analysis. Antennas can serve to connect the in-vehicle control system **150** and the real-time multi-object tracking module **200** with the data network **120** via cellular, satellite, radio, or other conventional signal reception mechanisms. Such cellular data networks are currently available (e.g., Verizon™, AT&T™, T-Mobile™, etc.). Such satellite-based data or content networks are also currently available (e.g., SiriusXM™, HughesNet™, etc.). The conventional broadcast networks, such as AM/FM radio networks, pager networks, UHF networks, gaming networks, WiFi networks, peer-to-peer networks, Voice over IP (VoIP) networks, and the like are also well-known. Thus, as described in more detail below, the in-vehicle control system **150** and the real-time multi-object tracking module **200** can receive web-based data or content via an in-vehicle web-enabled device interface **131**, which can be used to connect with the in-vehicle web-enabled device receiver **130** and network **120**. In this manner, the in-vehicle control system **150** and the real-time multi-object tracking module **200** can support a variety of network-connectable in-vehicle devices and systems from within a vehicle **105**.

As shown in FIG. **1**, the in-vehicle control system **150** and the real-time multi-object tracking module **200** can also receive data, image processing control parameters, and training content from user mobile devices **132**, which can be located inside or proximately to the vehicle **105**. The user mobile devices **132** can represent standard mobile devices, such as cellular phones, smartphones, personal digital assistants (PDA's), MP3 players, tablet computing devices (e.g., iPad™), laptop computers, CD players, and other mobile devices, which can produce, receive, and/or deliver data, image processing control parameters, and content for the in-vehicle control system **150** and the real-time multi-object tracking module **200**. As shown in FIG. **1**, the mobile devices **132** can also be in data communication with the network cloud **120**. The mobile devices **132** can source data and content from internal memory components of the mobile devices **132** themselves or from network resources **122** via network **120**. Additionally, mobile devices **132** can themselves include a GPS data receiver, accelerometers, WiFi triangulation, or other geo-location sensors or components in the mobile device, which can be used to determine the real-time geo-location of the user (via the mobile device) at any moment in time. In any case, the in-vehicle control system **150** and the real-time multi-object tracking module **200** can receive data from the mobile devices **132** as shown in FIG. **1**.

Referring still to FIG. **1**, the example embodiment of ecosystem **101** can include vehicle operational subsystems **140**. For embodiments that are implemented in a vehicle **105**, many standard vehicles include operational subsystems, such as electronic control units (ECUs), supporting monitoring/control subsystems for the engine, brakes, transmission, electrical system, emissions system, interior environment, and the like. For example, data signals communicated from the vehicle operational subsystems **140** (e.g., ECUs of the vehicle **105**) to the in-vehicle control system **150** via vehicle subsystem interface **141** may include information about the state of one or more of the components or subsystems of the vehicle **105**. In particular, the data signals, which can be communicated from the vehicle operational subsystems **140** to a Controller Area Network (CAN) bus of the vehicle **105**, can be received and processed by the in-vehicle control system **150** via vehicle subsystem interface **141**. Embodiments of the systems and methods described herein can be used with substantially any mechanized system that uses a CAN bus or similar data communications bus as defined herein, including, but not limited to, industrial equipment, boats, trucks, machinery, or automobiles; thus, the term “vehicle” as used herein can include any such mechanized systems. Embodiments of the systems and methods described herein can also be used with any systems employing some form of network data communications; however, such network communications are not required.

Referring still to FIG. **1**, the example embodiment of ecosystem **101**, and the vehicle operational subsystems **140** therein, can include a variety of vehicle subsystems in support of the operation of vehicle **105**. In general, the vehicle **105** may take the form of a car, truck, motorcycle, bus, boat, airplane, helicopter, lawn mower, earth mover, snowmobile, aircraft, recreational vehicle, amusement park vehicle, farm equipment, construction equipment, tram, golf cart, train, and trolley, for example. Other vehicles are possible as well. The vehicle **105** may be configured to operate fully or partially in an autonomous mode. For example, the vehicle **105** may control itself while in the autonomous mode, and may be operable to determine a current state of the vehicle and its environment, determine a predicted behavior of at least one other vehicle in the environment, determine a confidence level that may correspond to a likelihood of the at least one other vehicle to perform the predicted behavior, and control the vehicle **105** based on the determined information. While in autonomous mode, the vehicle **105** may be configured to operate without human interaction.

The vehicle **105** may include various vehicle subsystems such as a vehicle drive subsystem **142**, vehicle sensor subsystem **144**, vehicle control subsystem **146**, and occupant interface subsystem **148**. As described above, the vehicle **105** may also include the in-vehicle control system **150**, the computing system **170**, and the real-time multi-object tracking module **200**. The vehicle **105** may include more or fewer subsystems and each subsystem could include multiple elements. Further, each of the subsystems and elements of vehicle **105** could be interconnected. Thus, one or more of the described functions of the vehicle **105** may be divided up into additional functional or physical components or combined into fewer functional or physical components. In some further examples, additional functional and physical components may be added to the examples illustrated by FIG. **1**.

The vehicle drive subsystem **142** may include components operable to provide powered motion for the vehicle **105**. In an example embodiment, the vehicle drive subsystem **142** may include an engine or motor, wheels/tires, a transmission, an electrical subsystem, and a power source. The engine or motor may be any combination of an internal combustion engine, an electric motor, steam engine, fuel cell engine, propane engine, or other types of engines or motors.

In some example embodiments, the engine may be configured to convert a power source into mechanical energy. In some example embodiments, the vehicle drive subsystem **142** may include multiple types of engines or motors. For instance, a gas-electric hybrid car could include a gasoline engine and an electric motor. Other examples are possible.

The wheels of the vehicle **105** may be standard tires. The wheels of the vehicle **105** may be configured in various formats, including a unicycle, bicycle, tricycle, or a four-wheel format, such as on a car or a truck, for example. Other wheel geometries are possible, such as those including six or more wheels. Any combination of the wheels of vehicle **105** may be operable to rotate differentially with respect to other wheels. The wheels may represent at least one wheel that is fixedly attached to the transmission and at least one tire coupled to a rim of the wheel that could make contact with the driving surface. The wheels may include a combination of metal and rubber, or another combination of materials. The transmission may include elements that are operable to transmit mechanical power from the engine to the wheels. For this purpose, the transmission could include a gearbox, a clutch, a differential, and drive shafts. The transmission may include other elements as well. The drive shafts may include one or more axles that could be coupled to one or more wheels. The electrical system may include elements that are operable to transfer and control electrical signals in the vehicle **105**. These electrical signals can be used to activate lights, servos, electrical motors, and other electrically driven or controlled devices of the vehicle **105**. The power source may represent a source of energy that may, in full or in part, power the engine or motor. That is, the engine or motor could be configured to convert the power source into mechanical energy. Examples of power sources include gasoline, diesel, other petroleum-based fuels, propane, other compressed gas-based fuels, ethanol, fuel cell, solar panels, batteries, and other sources of electrical power. The power source could additionally or alternatively include any combination of fuel tanks, batteries, capacitors, or flywheels. The power source may also provide energy for other subsystems of the vehicle **105**.

The vehicle sensor subsystem **144** may include a number of sensors configured to sense information about an environment or condition of the vehicle **105**. For example, the vehicle sensor subsystem **144** may include an inertial measurement unit (IMU), a Global Positioning System (GPS) transceiver, a RADAR unit, a laser range finder/LIDAR unit, and one or more cameras or image capture devices. The vehicle sensor subsystem **144** may also include sensors configured to monitor internal systems of the vehicle **105** (e.g., an **02** monitor, a fuel gauge, an engine oil temperature). Other sensors are possible as well. One or more of the sensors included in the vehicle sensor subsystem **144** may be configured to be actuated separately or collectively in order to modify a position, an orientation, or both, of the one or more sensors.

The IMU may include any combination of sensors (e.g., accelerometers and gyroscopes) configured to sense position and orientation changes of the vehicle **105** based on inertial acceleration. The GPS transceiver may be any sensor configured to estimate a geographic location of the vehicle **105**. For this purpose, the GPS transceiver may include a receiver/transmitter operable to provide information regarding the position of the vehicle **105** with respect to the Earth. The RADAR unit may represent a system that utilizes radio signals to sense objects within the local environment of the vehicle **105**. In some embodiments, in addition to sensing the objects, the RADAR unit may additionally be configured to sense the speed and the heading of the objects proximate to the vehicle **105**. The laser range finder or LIDAR unit may be any sensor configured to sense objects in the environment in which the vehicle **105** is located using lasers. In an example embodiment, the laser range finder/LIDAR unit may include one or more laser sources, a laser scanner, and one or more detectors, among other system components. The laser range finder/LIDAR unit could be configured to operate in a coherent (e.g., using heterodyne detection) or an incoherent detection mode. The cameras may include one or more devices configured to capture a plurality of images of the environment of the vehicle **105**. The cameras may be still image cameras or motion video cameras.

The vehicle control system **146** may be configured to control operation of the vehicle **105** and its components. Accordingly, the vehicle control system **146** may include various elements such as a steering unit, a throttle, a brake unit, a navigation unit, and an autonomous control unit.

The steering unit may represent any combination of mechanisms that may be operable to adjust the heading of vehicle **105**. The throttle may be configured to control, for instance, the operating speed of the engine and, in turn, control the speed of the vehicle **105**. The brake unit can include any combination of mechanisms configured to decelerate the vehicle **105**. The brake unit can use friction to slow the wheels in a standard manner. In other embodiments, the brake unit may convert the kinetic energy of the wheels to electric current. The brake unit may take other forms as well. The navigation unit may be any system configured to determine a driving path or route for the vehicle **105**. The navigation unit may additionally be configured to update the driving path dynamically while the vehicle **105** is in operation. In some embodiments, the navigation unit may be configured to incorporate data from the real-time multi-object tracking module **200**, the GPS transceiver, and one or more predetermined maps so as to determine the driving path for the vehicle **105**. The autonomous control unit may represent a control system configured to identify, evaluate, and avoid or otherwise negotiate potential obstacles in the environment of the vehicle **105**. In general, the autonomous control unit may be configured to control the vehicle **105** for operation without a driver or to provide driver assistance in controlling the vehicle **105**. In some embodiments, the autonomous control unit may be configured to incorporate data from the real-time multi-object tracking module **200**, the GPS transceiver, the RADAR, the LIDAR, the cameras, and other vehicle subsystems to determine the driving path or trajectory for the vehicle **105**. The vehicle control system **146** may additionally or alternatively include components other than those shown and described.

Occupant interface subsystems **148** may be configured to allow interaction between the vehicle **105** and external sensors, other vehicles, other computer systems, and/or an occupant or user of vehicle **105**. For example, the occupant interface subsystems **148** may include standard visual display devices (e.g., plasma displays, liquid crystal displays (LCDs), touchscreen displays, heads-up displays, or the like), speakers or other audio output devices, microphones or other audio input devices, navigation interfaces, and interfaces for controlling the internal environment (e.g., temperature, fan, etc.) of the vehicle **105**.

In an example embodiment, the occupant interface subsystems **148** may provide, for instance, means for a user/occupant of the vehicle **105** to interact with the other vehicle subsystems. The visual display devices may provide information to a user of the vehicle **105**. The user interface devices can also be operable to accept input from the user via a touchscreen. The touchscreen may be configured to sense at least one of a position and a movement of a user's finger via capacitive sensing, resistance sensing, or a surface acoustic wave process, among other possibilities. The touchscreen may be capable of sensing finger movement in a direction parallel or planar to the touchscreen surface, in a direction normal to the touchscreen surface, or both, and may also be capable of sensing a level of pressure applied to the touchscreen surface. The touchscreen may be formed of one or more translucent or transparent insulating layers and one or more translucent or transparent conducting layers. The touchscreen may take other forms as well.

In other instances, the occupant interface subsystems **148** may provide means for the vehicle **105** to communicate with devices within its environment. The microphone may be configured to receive audio (e.g., a voice command or other audio input) from a user of the vehicle **105**. Similarly, the speakers may be configured to output audio to a user of the vehicle **105**. In one example embodiment, the occupant interface subsystems **148** may be configured to wirelessly communicate with one or more devices directly or via a communication network. For example, a wireless communication system could use 3G cellular communication, such as CDMA, EVDO, GSM/GPRS, or 4G cellular communication, such as WiMAX or LTE. Alternatively, the wireless communication system may communicate with a wireless local area network (WLAN), for example, using WIFI®. In some embodiments, the wireless communication system **146** may communicate directly with a device, for example, using an infrared link, BLUETOOTH®, or ZIGBEE®. Other wireless protocols, such as various vehicular communication systems, are possible within the context of the disclosure. For example, the wireless communication system may include one or more dedicated short range communications (DSRC) devices that may include public or private data communications between vehicles and/or roadside stations.

Many or all of the functions of the vehicle **105** can be controlled by the computing system **170**. The computing system **170** may include at least one data processor **171** (which can include at least one microprocessor) that executes processing instructions stored in a non-transitory computer readable medium, such as the data storage device **172**. The computing system **170** may also represent a plurality of computing devices that may serve to control individual components or subsystems of the vehicle **105** in a distributed fashion. In some embodiments, the data storage device **172** may contain processing instructions (e.g., program logic) executable by the data processor **171** to perform various functions of the vehicle **105**, including those described herein in connection with the drawings. The data storage device **172** may contain additional instructions as well, including instructions to transmit data to, receive data from, interact with, or control one or more of the vehicle drive subsystem **142**, the vehicle sensor subsystem **144**, the vehicle control subsystem **146**, and the occupant interface subsystems **148**.

In addition to the processing instructions, the data storage device **172** may store data such as image processing parameters, training data, roadway maps, and path information, among other information. Such information may be used by the vehicle **105** and the computing system **170** during the operation of the vehicle **105** in the autonomous, semi-autonomous, and/or manual modes.

The vehicle **105** may include a user interface for providing information to or receiving input from a user or occupant of the vehicle **105**. The user interface may control or enable control of the content and the layout of interactive images that may be displayed on a display device. Further, the user interface may include one or more input/output devices within the set of occupant interface subsystems **148**, such as the display device, the speakers, the microphones, or a wireless communication system.

The computing system **170** may control the function of the vehicle **105** based on inputs received from various vehicle subsystems (e.g., the vehicle drive subsystem **142**, the vehicle sensor subsystem **144**, and the vehicle control subsystem **146**), as well as from the occupant interface subsystem **148**. For example, the computing system **170** may use input from the vehicle control system **146** in order to control the steering unit to avoid an obstacle detected by the vehicle sensor subsystem **144** and the real-time multi-object tracking module **200**, move in a controlled manner, or follow a path or trajectory based on output generated by the real-time multi-object tracking module **200**. In an example embodiment, the computing system **170** can be operable to provide control over many aspects of the vehicle **105** and its subsystems.

Although FIG. **1** shows various components of vehicle **105**, e.g., vehicle subsystems **140**, computing system **170**, data storage device **172**, and real-time multi-object tracking module **200**, as being integrated into the vehicle **105**, one or more of these components could be mounted or associated separately from the vehicle **105**. For example, data storage device **172** could, in part or in full, exist separate from the vehicle **105**. Thus, the vehicle **105** could be provided in the form of device elements that may be located separately or together. The device elements that make up vehicle **105** could be communicatively coupled together in a wired or wireless fashion.

Additionally, other data and/or content (denoted herein as ancillary data) can be obtained from local and/or remote sources by the in-vehicle control system **150** as described above. The ancillary data can be used to augment, modify, or train the operation of the real-time multi-object tracking module **200** based on a variety of factors including, the context in which the user is operating the vehicle (e.g., the location of the vehicle, the specified destination, direction of travel, speed, the time of day, the status of the vehicle, etc.), and a variety of other data obtainable from the variety of sources, local and remote, as described herein.

In a particular embodiment, the in-vehicle control system **150** and the real-time multi-object tracking module **200** can be implemented as in-vehicle components of vehicle **105**. In various example embodiments, the in-vehicle control system **150** and the real-time multi-object tracking module **200** in data communication therewith can be implemented as integrated components or as separate components. In an example embodiment, the software components of the in-vehicle control system **150** and/or the real-time multi-object tracking module **200** can be dynamically upgraded, modified, and/or augmented by use of the data connection with the mobile devices **132** and/or the network resources **122** via network **120**. The in-vehicle control system **150** can periodically query a mobile device **132** or a network resource **122** for updates or updates can be pushed to the in-vehicle control system **150**.

System and Method for Online Real-Time Multi-Object Tracking

A system and method for online real-time multi-object tracking are disclosed. In various example embodiments described herein, we introduce an online real-time multi-object tracking system, which achieves state-of-the-art performance at a real-time speed of over 30 frames per second (FPS). The example system and method for online real-time multi-object tracking as disclosed herein can provide an online real-time MOT method, where each object is modeled by a finite state machine (FSM). Matching objects among image frames in a video feed can be considered as a transition in the finite state machine. Additionally, the various example embodiments can also extract motion features and appearance features for each object to improve tracking performance. Moreover, a Kalman filter can be used to reduce the noise from the results of the object detection.

In the example embodiment, each object in a video feed is modeled by a finite state machine, and the whole tracking process is divided into four stages: 1) similarity calculation, 2) data association, 3) state transition, and 4) post processing. In the first stage, the similarity between an object template or previous object data and an object detection result is calculated. Data indicative of this similarity is used for data association in the second stage. The data association of the second stage can use the similarity data to find the optimal or best matching between previous object data and the object detection results in the current image frame. Then, each object transitions its state according to the results of the data association. Finally, a post processing operation is used to smooth the bounding boxes for each object in the final tracking output.

FIG. **2** illustrates a single object modeled by a finite state machine, and a method used in an example embodiment to perform multi-object tracking. The example embodiment can be configured to model each single object by a finite state machine. This model can be used in the example embodiment to perform multi-object tracking as described in more detail below. In an example embodiment illustrated in FIG. **2**, there are four FSM states for each object: initialized, tracked, lost, and removed. FIG. **2** shows the four states and how they are related to each other. Each state of the example embodiment is described below with reference to FIG. **2**.

Initialized State

A new object detected in the video feed that has never been tracked before is set to the initialized state in its finite state machine. Thus, when a new object is detected by image analysis and object detection, the new object is initialized in the initialized state as a new tracking object. Because there may be some false positives in the detection results, it is possible that the new object is a false positive object detection. In order to avoid false positive object detections, we use a learning based method (such as XGBoost, Support Vector Machine, etc.) to train a classifier (here we call it the initialization classifier), so that we can judge if the detection result is a false positive. The features we use to train the initialization classifier include both vision features and bounding box information related to the detection result. Specifically, given a detection result (e.g., a bounding box position and a confidence score), vision features such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) can be extracted from the bounding box of the detected object. Then, the vision feature can be combined with the detection confidence score to feed the classifier.

By using the initialization classifier, we can determine whether a new object detection result is a false positive. If the new object detection result is a real object (e.g., not a false positive), the new object detection result transitions from the initialized state to the tracked state (described below). If the new object detection result is not a real object (e.g., a false positive), the new object detection result transitions from the initialized state to the removed state (also described below).

Tracked State

When a new image frame is received, objects currently in the tracked state need to be processed to determine if the objects currently in the tracked state can remain in the tracked state or should transition to the lost state. This determination depends on the matching detection results from a comparison of a prior image frame with the detection results for the new image frame. Specifically, given a new image frame from the video feed, the example embodiment can match all tracked and lost objects from the prior image frame with the detection results in the new image frame (this is called data association). As a result of this matching or data association process, some previously tracked objects may be lost in the new image frame. Other previously tracked objects may continue to be tracked in the current image frame. Other previously lost objects may re-appear to be tracked again. The detailed matching strategy is described below in connection with the description of the feature extraction and template updating strategies.

Feature Extraction

In an example embodiment, there are two kinds of features used for object data association: motion feature and appearance feature. For motion feature, a Kalman filter is set for each object in tracking history. When a new image frame is received, the Kalman filter can predict a bounding box position for an object in the new image frame according to the trajectory of the object. Then, the example embodiment can determine a similarity (or difference) score between the predicted bounding box position for an object by the Kalman filter and the position of each bounding box for objects detected in the detection results for the new image frame. In a tracking system of an example embodiment, we use Intersection Over Union (IOU) as the similarity score; because, IOU can describe the shape similarity between two bounding boxes. This similarity score is considered as the motion feature or motion similarity of a detected object.

The second part of the feature extraction used in an example embodiment is the appearance feature for each object. The appearance feature is a key feature to distinguish one object from another object. The appearance feature can be extracted by a pre-trained convolutional neural network (CNN). In other embodiments, the appearance feature can be extracted by use of hand-craft features or vision features, such as HOG and SIFT. Different features are suitable for different scenarios or applications of the technology. As such, the methods used for appearance feature extraction can vary to obtain the best performance for different applications. Once the appearance feature for a current object is extracted, the appearance feature of the object can be used to determine an appearance similarity (or difference) as related to the appearance features of previous objects and prior detection results from prior image frames.

Template Updating

If a currently detected object is successfully matched with a bounding box of a previously detected object, the example embodiment can update the appearance feature for the current object as its template. Specifically, the example embodiment can obtain the appearance feature extracted from the matching object bounding box and use the extracted appearance feature as the new template of the current object. In the example embodiment, we do not directly replace the old template with the new appearance feature; instead, the example embodiment keeps several templates (usually three) for each object that has ever been tracked.

When a template is updated, the example embodiment can set a similarity threshold and a bounding box confidence threshold. Only appearance features satisfying the following two conditions can be used to update an old template: First, the similarity score between the appearance feature for the current object and the old template should be less than the similarity threshold. This is because a low similarity score usually means the object has been changed a lot in the current image frame, so that the template should be updated. Second, the detection bounding box confidence level should be higher than the bounding box confidence threshold. This is because we need to avoid false positives in the detection results, and a bounding box with a low confidence level is more likely to be a false positive.

If an appearance feature is selected to be a new template, the example embodiment can determine which of the old templates should be replaced. There are several strategies that can be used for this purpose, such as a Least Recent Use (LRU) strategy, or a strategy that just replaces the oldest template in the template pool.

Lost State

Similar to the tracked state, there are three different kinds of transitions an object can make from the lost state. First, if the object is successfully matched with a detection result in the current image frame, the object will transition back to the tracked state from the lost state. Second, if there is no matching for this object, the object will remain in the lost state. Third, if the object has remained in the lost state for a number of cycles that is greater than a threshold, the object transitions from the lost state to the removed state, where the object is considered to have disappeared.

Because there is no matching detection result for an object in the lost state, the example embodiment does not update the appearance feature (e.g., the template) for these lost objects. However, the example embodiment does need to keep predicting the bounding box position by use of the Kalman filter; because, the example embodiment can use the motion feature for lost objects to perform data association in case the lost object re-appears in a new image frame. This is called a blind update.

Removed State

In an example embodiment, there are only two ways for an object to transition into the removed state. First, an object in the initialized state for which a detection result is considered to be a false positive transitions into the removed state. Second, an object that has remained in the lost state for too cycles transitions into the removed state and is considered to have disappeared from the camera view.

In various example embodiments, a threshold can be used to determine if an object has disappeared. In some embodiments, the larger the threshold is, the higher the tracking performance will be; because, sometimes an object disappears for a while and then may come back into view again. However, a larger threshold leads to a low tracking speed; because, there are more objects in the lost state and more processing overhead is needed to perform object matching during the period of data association. As such, there exists a trade-off between performance and speed.

Tracking Process

FIG. **3** is an operational flow diagram **300** illustrating an example embodiment of a system and method for online real-time multi-object tracking. In the example embodiment as described above, each object in a video feed can be modeled by a finite state machine. Additionally, the tracking process of an example embodiment can be divided into four stages: 1) similarity calculation, 2) data association, 3) state transition, and 4) post processing. The tracking process of the example embodiment can be used when a new image frame and its corresponding detection results are received.

Each of the stages of the tracking process of the example embodiment are described below with reference to FIG. **3**.

Similarity Calculation

With reference to block **310** shown in FIG. **3**, when a new image frame is received from a video feed, the example embodiment is configured to determine the similarity of each object as related to object detection results. As described above, there are two kinds of features used to determine object similarity in an example embodiment: motion feature similarity and appearance feature similarity. In one example embodiment, motion feature similarity is calculated as the IOU of the prediction of the Kalman filter and the detected object bounding box position. The appearance feature similarity is calculated as the Euclidean distance between the object template and the appearance feature of the object detection result. Because there are several templates retained for each object, the example embodiment can be configured to choose one of the several object templates to be used for data association. There are several strategies that can be used to choose appearance similarity, such as mean or max similarity. Once the similarities for each object have been calculated, the similarities can be used for data association (described below) to find matchings between objects and detection results.

Data Association

With reference to block **320** shown in FIG. **3**, the similarities of all pairs of object and detection results have been determined in the similarity calculation stage described above. In the data association phase, the example embodiment is configured to find the best matchings between objects of previous image frames and detection results from a current image frame. In particular, the example embodiment is configured to find the positions of previously detected objects in the current image frame. Because the best matchings require an optimal or best matching solution, an example embodiment can use a Hungarian algorithm (which is also called Kuhn-Munkres algorithm or Munkres assignment algorithm) to find the best matchings, where the similarity scores calculated in a last step of the process are considered as costs or weights in the Hungarian algorithm. The use of the Hungarian algorithm, or other best matching process, can identify pairs of matchings between objects and detection results. Then, the example embodiment can filter out those pairs whose similarity score is less than a predefined threshold. As a result of the data association process, three kinds of results can be obtained: matched pairs of object and detection result **332**, unmatched objects **334**, and unmatched detection results **336**. These results can be used to effect state transitions in the finite state machines for each object as described below.

State Transition

With reference to blocks **330** shown in FIG. **3**, after the data association stage is completed, the example embodiment can use the data association results to effect state transitions in the finite state machines for each object. The example embodiment can also initialize new objects for unmatched detection results. As shown in block **332** of FIG. **3**, for each object having a matched detection result, the object (or its FSM) transitions to the tracked state. In block **338**, the template and the Kalman filter for the object is updated for the corresponding detection result. As shown in block **334** of FIG. **3**, for each unmatched object, the object (or its FSM) transitions to the lost state if the prior state of the object was the tracked state. If the prior state of the object was the lost state, the lost object can be processed as described above to determine if the object should be transitioned to the removed state. In block **338**, the template and the Kalman filter for the object is updated by blind update. As shown in block **336** of FIG. **3**, for each unmatched detection result, the example embodiment can initialize a new object and transition the new object to the initialized state as described above. In block **338**, the template and the Kalman filter for the new object is updated for the corresponding detection result.

Post Processing

Because almost all related tracking methods directly use the bounding boxes of detection results as the final output for each image frame, and detection results for each object may be unstable, there may be some variations in the final output. In order to avoid this problem and make the final output smoother, some modifications to the detection results can be made in the example embodiment. Specifically, we can use the weighted average of the detection result and the prediction of Kalman filter as the final tracking output, which can improve the tracking performance both in benchmark and visualization.

FIG. **4** illustrates components of the system for online real-time multi-object tracking of an example embodiment. Referring now to FIG. **4**, an example embodiment disclosed herein can be used in the context of an online real-time multi-object tracking system **210** for autonomous vehicles. The online real-time multi-object tracking system **210** can be included in or executed by the real-time multi-object tracking module **200** as described above. The online real-time multi-object tracking system **210** can include a similarity calculation module **212**, a data association module **214**, a state transition module **216** with corresponding object finite state machines **217**, and a post processing module **218**. These modules can be implemented as processing modules, software or firmware elements, processing instructions, or other processing logic embodying any one or more of the methodologies or functions described and/or claimed herein. The online real-time multi-object tracking system **210** can receive one or more image streams or image frame data sets from a camera or other image source of the autonomous vehicle **105**. As described above, the similarity calculation module **212** can calculate the similarity between an object template or previous object data and an object detection result. Data indicative of this similarity is used for data association. The data association module **214** can use the similarity data to find the optimal or best matching between previous object data and the object detection results in the current image frame. Then, the state transition module **216** can cause the FSM **217** for each object to transition its state according to the results of the data association. Finally, the post processing module **218** can be used to smooth the bounding boxes for each object in the final object tracking output. The online real-time multi-object tracking system **210** can provide as an output the object tracking output data **220** generated as described above.

Referring now to FIG. **5**, a process flow diagram illustrates an example embodiment of a system and method for online real-time multi-object tracking. The example embodiment can be configured to: receive image frame data from at least one camera associated with an autonomous vehicle (processing block **1010**); generate similarity data corresponding to a similarity between object data in a previous image frame compared with object detection results from a current image frame (processing block **1020**); use the similarity data to generate data association results corresponding to a best matching between the object data in the previous image frame and the object detection results from the current image frame (processing block **1030**); cause state transitions in finite state machines for each object according to the data association results (processing block **1040**); and provide as an output object tracking output data corresponding to the states of the finite state machines for each object (processing block **1050**).

As used herein and unless specified otherwise, the term "mobile device" includes any computing or communications device that can communicate with the in-vehicle control system **150** and/or the real-time multi-object tracking module **200** described herein to obtain read or write access to data signals, messages, or content communicated via any mode of data communications. In many cases, the mobile device **130** is a handheld, portable device, such as a smart phone, mobile phone, cellular telephone, tablet computer, laptop computer, display pager, radio frequency (RF) device, infrared (IR) device, global positioning device (GPS), Personal Digital Assistants (PDA), handheld computers, wearable computer, portable game console, other mobile communication and/or computing device, or an integrated device combining one or more of the preceding devices, and the like. Additionally, the mobile device **130** can be a computing device, personal computer (PC), multiprocessor system, microprocessor-based or programmable consumer electronic device, network PC, diagnostics equipment, a system operated by a vehicle **119** manufacturer or service technician, and the like, and is not limited to portable devices. The mobile device **130** can receive and process data in any of a variety of data formats. The data format may include or be configured to operate with any programming format, protocol, or language including, but not limited to, JavaScript, C++, iOS, Android, etc.

As used herein and unless specified otherwise, the term "network resource" includes any device, system, or service that can communicate with the in-vehicle control system **150** and/or the real-time multi-object tracking module **200** described herein to obtain read or write access to data signals, messages, or content communicated via any mode of inter-process or networked data communications. In many cases, the network resource **122** is a data network accessible computing platform, including client or server computers, websites, mobile devices, peer-to-peer (P2P) network nodes, and the like. Additionally, the network resource **122** can be a web appliance, a network router, switch, bridge, gateway, diagnostics equipment, a system operated by a vehicle **119** manufacturer or service technician, or any machine capable of executing a set of instructions (sequential or otherwise) that specify actions to be taken by that machine. Further, while only a single machine is illustrated, the term "machine" can also be taken to include any collection of machines that individually or jointly execute a set (or multiple sets) of instructions to perform any one or more of the methodologies discussed herein. The network resources **122** may include any of a variety of providers or processors of network transportable digital content. Typically, the file format that is employed is Extensible Markup Language (XML), however, the various embodiments are not so limited, and other file formats may be used. For example, data formats other than Hypertext Markup Language (HTML)/XML or formats other than open/standard data formats can be supported by various embodiments. Any electronic file format, such as Portable Document Format (PDF), audio (e.g., Motion Picture Experts Group Audio Layer 3—MP3, and the like), video (e.g., MP4, and the like), and any proprietary interchange format defined by specific content sites can be supported by the various embodiments described herein.

The wide area data network **120** (also denoted the network cloud) used with the network resources **122** can be configured to couple one computing or communication device with another computing or communication device. The network may be enabled to employ any form of computer readable data or media for communicating information from one electronic device to another. The network **120** can include the Internet in addition to other wide area networks (WANs), cellular telephone networks, metro-area networks, local area networks (LANs), other packet-switched networks, circuit-switched networks, direct data connections, such as through a universal serial bus (USB) or Ethernet port, other forms of computer-readable media, or any combination thereof. The network **120** can include the Internet in addition to other wide area networks (WANs), cellular telephone networks, satellite networks, over-the-air broadcast networks, AM/FM radio networks, pager networks, UHF networks, other broadcast networks, gaming networks, WiFi networks, peer-to-peer networks, Voice Over IP (VoIP) networks, metro-area networks, local area networks (LANs), other packet-switched networks, circuit-switched networks, direct data connections, such as through a universal serial bus (USB) or Ethernet port, other forms of computer-readable media, or any combination thereof. On an interconnected set of networks, including those based on differing architectures and protocols, a router or gateway can act as a link between networks, enabling messages to be sent between computing devices on different networks. Also, communication links within networks can typically include twisted wire pair cabling, USB, Firewire, Ethernet, or coaxial cable, while communication links between networks may utilize analog or digital telephone lines, full or fractional dedicated digital lines including T1, T2, T3, and T4, Integrated Services Digital Networks (ISDNs), Digital User Lines (DSLs), wireless links including satellite links, cellular telephone links, or other communication links known to those of ordinary skill in the art. Furthermore, remote computers and other related electronic devices can be remotely connected to the network via a modem and temporary telephone link.

The network **120** may further include any of a variety of wireless sub-networks that may further overlay stand-alone ad-hoc networks, and the like, to provide an infrastructure-oriented connection. Such sub-networks may include mesh networks, Wireless LAN (WLAN) networks, cellular networks, and the like. The network may also include an autonomous system of terminals, gateways, routers, and the like connected by wireless radio links or wireless transceivers. These connectors may be configured to move freely and randomly and organize themselves arbitrarily, such that the topology of the network may change rapidly. The network **120** may further employ one or more of a plurality of standard wireless and/or cellular protocols or access technologies including those set forth herein in connection with network interface **712** and network **714** described in the figures herewith.

In a particular embodiment, a mobile device **132** and/or a network resource **122** may act as a client device enabling a user to access and use the in-vehicle control system **150** and/or the real-time multi-object tracking module **200** to interact with one or more components of a vehicle subsystem. These client devices **132** or **122** may include virtually any computing device that is configured to send and receive information over a network, such as network **120** as described herein. Such client devices may include mobile devices, such as cellular telephones, smart phones, tablet computers, display pagers, radio frequency (RF) devices, infrared (IR) devices, global positioning devices (GPS), Personal Digital Assistants (PDAs), handheld computers, wearable computers, game consoles, integrated devices combining one or more of the preceding devices, and the like. The client devices may also include other computing devices, such as personal computers (PCs), multiprocessor systems, microprocessor-based or programmable consumer electronics, network PC's, and the like. As such, client devices may range widely in terms of capabilities and features. For example, a client device configured as a cell phone may have a numeric keypad and a few lines of monochrome LCD display on which only text may be displayed. In another example, a web-enabled client device may have a touch sensitive screen, a stylus, and a color LCD display screen in which both text and graphics may be displayed. Moreover, the web-enabled client device may include a browser application enabled to receive and to send wireless application protocol messages (WAP), and/or wired application messages, and the like. In one embodiment, the browser application is enabled to employ HyperText Markup Language (HTML), Dynamic HTML, Handheld Device Markup Language (HDML), Wireless Markup Language (WML), WMLScript, JavaScript™, EXtensible HTML (xHTML), Compact HTML (CHTML), and the like, to display and send a message with relevant information.

The client devices may also include at least one client application that is configured to receive content or messages from another computing device via a network transmission. The client application may include a capability to provide and receive textual content, graphical content, video content, audio content, alerts, messages, notifications, and the like. Moreover, the client devices may be further configured to communicate and/or receive a message, such as through a Short Message Service (SMS), direct messaging (e.g., Twitter), email, Multimedia Message Service (MMS), instant messaging (IM), internet relay chat (IRC), mIRC, Jabber, Enhanced Messaging Service (EMS), text messaging, Smart Messaging, Over the Air (OTA) messaging, or the like, between another computing device, and the like. The client devices may also include a wireless application device on which a client application is configured to enable a user of the device to send and receive information to/from network resources wirelessly via the network.

The in-vehicle control system **150** and/or the real-time multi-object tracking module **200** can be implemented using systems that enhance the security of the execution environment, thereby improving security and reducing the possibility that the in-vehicle control system **150** and/or the real-time multi-object tracking module **200** and the related services could be compromised by viruses or malware. For example, the in-vehicle control system **150** and/or the real-time multi-object tracking module **200** can be implemented using a Trusted Execution Environment, which can ensure that sensitive data is stored, processed, and communicated in a secure way.

FIG. **6** shows a diagrammatic representation of a machine in the example form of a computing system **700** within which a set of instructions when executed and/or processing logic when activated may cause the machine to perform any one or more of the methodologies described and/or claimed herein. In alternative embodiments, the machine operates as a standalone device or may be connected (e.g., networked) to other machines. In a networked deployment, the machine may operate in the capacity of a server or a client machine in server-client network environment, or as a peer machine in a peer-to-peer (or distributed) network environment. The machine may be a personal computer (PC), a laptop computer, a tablet computing system, a Personal Digital Assistant (PDA), a cellular telephone, a smartphone, a web appliance, a set-top box (STB), a network router, switch or bridge, or any machine capable of executing a set of instructions (sequential or otherwise) or activating processing logic that specify actions to be taken by that machine. Further, while only a single machine is illustrated, the term "machine" can also be taken to include any collection of machines that individually or jointly execute a set (or multiple sets) of instructions or processing logic to perform any one or more of the methodologies described and/or claimed herein.

The example computing system **700** can include a data processor **702** (e.g., a System-on-a-Chip (SoC), general processing core, graphics core, and optionally other processing logic) and a memory **704**, which can communicate with each other via a bus or other data transfer system **706**. The mobile computing and/or communication system **700** may further include various input/output (I/O) devices and/or interfaces **710**, such as a touchscreen display, an audio jack, a voice interface, and optionally a network interface **712**. In an example embodiment, the network interface **712** can include one or more radio transceivers configured for compatibility with any one or more standard wireless and/or cellular protocols or access technologies (e.g., 2nd (2G), 2.5, 3rd (3G), 4th (4G) generation, and future generation radio access for cellular systems, Global System for Mobile communication (GSM), General Packet Radio Services (GPRS), Enhanced Data GSM Environment (EDGE), Wideband Code Division Multiple Access (WCDMA), LTE, CDMA2000, WLAN, Wireless Router (WR) mesh, and the like). Network interface **712** may also be configured for use with various other wired and/or wireless communication protocols, including TCP/IP, UDP, SIP, SMS, RTP, WAP, CDMA, TDMA, UMTS, UWB, WiFi, WiMax, Bluetooth©, IEEE 802.11x, and the like. In essence, network interface **712** may include or support virtually any wired and/or wireless communication and data processing mechanisms by which information/data may travel between a computing system **700** and another computing or communication system via network **714**.

The memory **704** can represent a machine-readable medium on which is stored one or more sets of instructions, software, firmware, or other processing logic (e.g., logic **708**) embodying any one or more of the methodologies or functions described and/or claimed herein. The logic **708**, or a portion thereof, may also reside, completely or at least partially within the processor **702** during execution thereof by the mobile computing and/or communication system **700**. As such, the memory **704** and the processor **702** may also constitute machine-readable media. The logic **708**, or a portion thereof, may also be configured as processing logic or logic, at least a portion of which is partially implemented in hardware. The logic **708**, or a portion thereof, may further be transmitted or received over a network **714** via the network interface **712**. While the machine-readable medium of an example embodiment can be a single medium, the term "machine-readable medium" should be taken to include a single non-transitory medium or multiple non-transitory media (e.g., a centralized or distributed database, and/or associated caches and computing systems) that store the one or more sets of instructions. The term "machine-readable medium" can also be taken to include any non-transitory medium that is capable of storing, encoding or carrying a set of instructions for execution by the machine and that cause the machine to perform any one or more of the methodologies of the various embodiments, or that is capable of storing, encoding or carrying data structures utilized by or associated with such a set of instructions. The term "machine-readable medium" can accordingly be taken to include, but not be limited to, solid-state memories, optical media, and magnetic media.

The Abstract of the Disclosure is provided to allow the reader to quickly ascertain the nature of the technical disclosure. It is submitted with the understanding that it will not be used to interpret or limit the scope or meaning of the claims. In addition, in the foregoing Detailed Description, it can be seen that various features are grouped together in a single embodiment for the purpose of streamlining the disclosure. This method of disclosure is not to be interpreted as reflecting an intention that the claimed embodiments require more features than are expressly recited in each claim. Rather, as the following claims reflect, inventive subject matter lies in less than all features of a single disclosed embodiment. Thus, the following claims are hereby incorporated into the Detailed Description, with each claim standing on its own as a separate embodiment.

What is claimed is:

1. An apparatus comprising:

at least one processor; and

at least one memory including computer program code, the at least one memory and the computer program code configured to, with the at least one processor, cause the apparatus to:

receive image data;

detect objects in the image data;

generate similarity data corresponding to a similarity between objects detected in a first frame of the image data compared with objects detected in a second frame of the image data;

maintain a template for each of the objects detected in the image data; and

match the objects detected in the first frame with the objects detected in the second frame based on the similarity data.

2. The apparatus of claim **1**, wherein the image data is received from at least one camera.

3. The apparatus of claim **2**, wherein the at least one camera is coupled to an autonomous vehicle.

4. The apparatus of claim **1** wherein the at least one memory and computer program code are configured to, with the at least one processor, further cause the apparatus to:

extract an appearance feature from each of the objects detected in the image data.

5. The apparatus of claim **4** wherein the appearance feature is extracted by a convolutional neural network.

6. The apparatus of claim **4** wherein to generate the similarity data, the at least one memory and computer program code are configured to, with the at least one processor, further cause the apparatus to:

calculate a Euclidean distance between the appearance feature of an object defined as the template and the appearance feature of the detected objects; and

generate the similarity data based on the calculated Euclidean distance.

7. The apparatus of claim **4** wherein the template corresponds to the appearance feature extracted from each of the objects.

8. The apparatus of claim **4** wherein the similarity data is generated based on a motion feature similarity and an appearance feature similarity.

9. The apparatus of claim **8** wherein the at least one memory and computer program code are configured to, with the at least one processor, further cause the apparatus to:

determine a similarity score for a detected object and a templated object based on the appearance feature;

determine whether the similarity score is less than a first threshold; and

determine whether a confidence level of a bounding box of the detected object is greater than a second threshold, wherein the template is updated in response to the determination that the similarity score is less than the first threshold and the confidence level is greater than the second threshold.

10. The apparatus of claim **8** wherein the motion feature similarity is based on a prediction of a Kalman filter and a bounding box position of a detected object.

11. The apparatus of claim **1** wherein to maintain the template of each of the objects detected in the image data, the at least one memory and computer program code are configured to, with the at least one processor, further cause the apparatus to:

update the template based on the similarity data.

12. The apparatus of claim **1** wherein the at least one memory and computer program code are configured to, with the at least one processor, further cause the apparatus to:

create a finite state machine for each of the objects detected in the image data, wherein the finite state machine for each of the objects represents a current detection state, wherein the current detection state comprises one of a plurality of possible object detection states for a corresponding object.

13. A method comprising:

receiving image data;

detecting objects in the image data;

generating similarity data corresponding to a similarity between objects detected in a first frame of the image data compared with objects detected in a second frame of the image data;

maintaining a template for each of the objects detected in the image data; and

matching the objects detected in the first frame with the objects detected in the second frame based on the similarity data.

14. The method of claim **13**, further comprising generating, based on the similarity data, match results corresponding to a best match between the objects in the first frame and the objects in the second frame.

15. The method of claim **14**, further comprising causing state transitions in finite state machines for each of the objects according to the match results.

16. The method of claim **15**, wherein the finite state machines for each of the objects comprise states from the group consisting of: initialized, tracked, lost, and removed.

17. The method of claim **15**, further comprising generating output data corresponding to states of the finite state machines for each of the objects.

18. The method of claim **17**, further comprising smoothing the output data.

19. The method of claim **17**, wherein the output data is adjusted based on a weighted average calculation for data of the objects detected, or a prediction of a Kalman filter.

20. A non-transitory computer-readable medium including computer program instructions which, when executed by at least one processor, cause the at least one processor to:

receive image data;

detect objects in the image data;

generate similarity data corresponding to a similarity between objects detected in a first frame of the image data compared with objects detected in a second frame of the image data;

maintain a template for each of the objects detected in the image data; and match the objects detected in the first frame with the objects detected in the second frame based on the similarity data.

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